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INTEGRATING LARGE LANGUAGE MODELS INTO AGENT MODELS FOR MULTI-AGENT SIMULATIONS: PRELIMINARY REPORT

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ABSTRACT

There have been active attempts to integrate agents backed by large language models into various intelligent systems. In this paper, we describe our work on integrating an LLM into an agent model for multi-agent simulations (MASs). One long-term goal in implementing an MAS has been constructing a computational model that accurately simulates fine-grained human behaviors within the target environment. Building a model capable of capturing and reproducing the individual characteristics of a diverse range of people has been challenging, both in terms of implementation cost and complexity. We propose a method that uses an LLM to generate behavior individuality, and enables on the spot decision making based on the surrounding environment. We implement an MAS that uses agents based on the proposed method and verify the validity of their behaviors.

1 INTRODUCTION

Multi-Agent Simulations (MASs) have been extensively researched in various application domains as a promising technique for constructing virtual social environments and analyzing the behavior of complex social phenomena and social systems. In recent years, for instance, MAS has been utilized for evaluating various measures before and after the COVID-19 pandemic outbreak, such as predicting the spread of infection based on vaccination rates (Kurahashi 2023). Additionally, MASs have been employed for the pre-verification of effective operational methods for analyzing and verifying the impact of bicycle-sharing services on the mobility of people in urban areas (Sánchez et al. 2022). As demonstrated by these examples, MAS is increasingly seen as a promising technology to support the design and implementation of policies and systems in support of human society.

MAS is a form of simulation that computes sequences of interactions among agents, which represent entities like humans or intelligent artifacts (*e.g.,* robots). How to construct agent models is a crucial technical challenge that determines simulation performance. When the goal of an MAS is to understand complex social phenomena or analyze social systems, it is considered effective to construct agent models that follow the KISS principle (Axelrod 1984), favoring coarse-grained and higher levels of abstraction. This is because it facilitates the analysis of causal relationships between individual behaviors and the emergent phenomena arising from their interactions. However, when the purpose of MAS is the design and verification of policies or systems intended for real-world application, fine-grained and concrete agent models are required to provide useful information for policy-maker's decision-making and gain public acceptance. Abstract models that ignore the characteristics of individuals leads to a divergence from stakeholders' goals and makes it difficult to thoroughly verify the societal impact of novel policies or systems.

The bottleneck in constructing fine-grained agent models lies in developing models that reproduce diverse and detailed behaviors for each target/purpose of the simulation with reasonable development costs. As each simulation is conducted assuming a different scenario and environmental information, building diverse agent models that make reasonable decisions based on individual objectives and preferences in constantly changing situations is not easy. Obtaining sufficient data to capture the diversity of behaviors in agent modeling is not always feasible, and modeling based on methods like subject interviews incurs substantial operational costs.

This paper proposes an approach based on the use of Large Language Models (LLMs) to construct agent models that can well simulate human behavior while minimizing development costs. It aims to achieve diverse and plausible behavioral characteristics and context-sensitive decision-making based on the surrounding environment. Here, LLMs, a form of collective knowledge, are expected to incorporate information about various behaviors humans may exhibit in different real-world situations. In this paper, we build MAS agents with LLMs, thus enabling agents to make decisions using LLM-mediated processes. Specifically, we create agent models capable of planning and executing actions to replicate pedestrians in a virtual food court with multiple eateries. Through integration with LLMs, we provide the agents with the ability to determine preferred actions based on natural language-based thought processes; the behavioral changes appropriate for the attributes set for each agent are validated.

2 RELATED WORKS

2.1 MAS and Agent Modeling for Human Mobility

Extensive research has been conducted on MAS for human mobility, with traffic being a prominent application area. The ASEP model, for instance, is a notable example that attempts to represent vehicle movement and analyze phenomena like traffic congestion (Nagel and Schreckenberg 1992). In the ASEP model, roads are modeled as a series of contiguous cells, with vehicles represented as discrete objects moving within individual cells. The state of each road is updated by the movements of vehicle-like objects in accordance with simple movement rules, which allows traffic flows to be replicated. The ASEP model has been reported to approximate real traffic flow effectively. However, the ASEP model, which discretely represents the continuous movement of vehicles and processes interactions between them based on simplified rules, is highly abstract and diverges from reality. On the other hand, the study (Hattori et al. 2011) has observed human driving behavior in realistic driving environments using driving simulators; the aim was to capture human decision-making in specific driving conditions and create realistic computational models of drivers. While the methods proposed have demonstrated reasonable performance in reproducing human driving behaviors, the cost associated with modeling, such as establishing driving simulation environments for behavior collection and analyzing data from numerous subjects, makes it challenging to employ them for each new simulation target. In other studies (Cheng and Nguyen 2011; Kumar et al. 2023), the focus was narrowed down to taxis, and taxi travel was modeled based on accumulated probe data. However, these approaches are limited to assigning parameters based on statistical data derived from aggregated travel data, and so fail to represent individual driver behaviors. The incorporated agent models rely on uniformly rational decision-making models.

The study (Fujii et al. 2017) proposed a MAS for mixed traffic based on interactions between pedestrians and vehicles. The agent modeling concept proposed in this paper is an expansion of the famous Social Force Model to generate reasonable pedestrian flows, where pedestrian-like agents continuously calculate their movement direction and speed within the MAS process to produce natural pedestrian flows. Each pedestrian agent is assigned only spatial position information and information for determining contact with other agents, individual preferences were ignored. While this method does not represent the diversity of pedestrian behavior characteristics, it offers efficient execution of mixed pedestrian-vehicle simulations. Another work dealing with pedestrians proposed a pedestrian model in which the movement of pedestrians represented in two-dimensional information was compressed into one-dimensional information; to prioritize computational speed over representational accuracy, a high level of abstraction was employed (Yamashita et al. 2013).

In contrast to modeling approaches that prioritize development costs and execution efficiency, such as those mentioned above, our approach seeks to represent the diversity of human behavior.

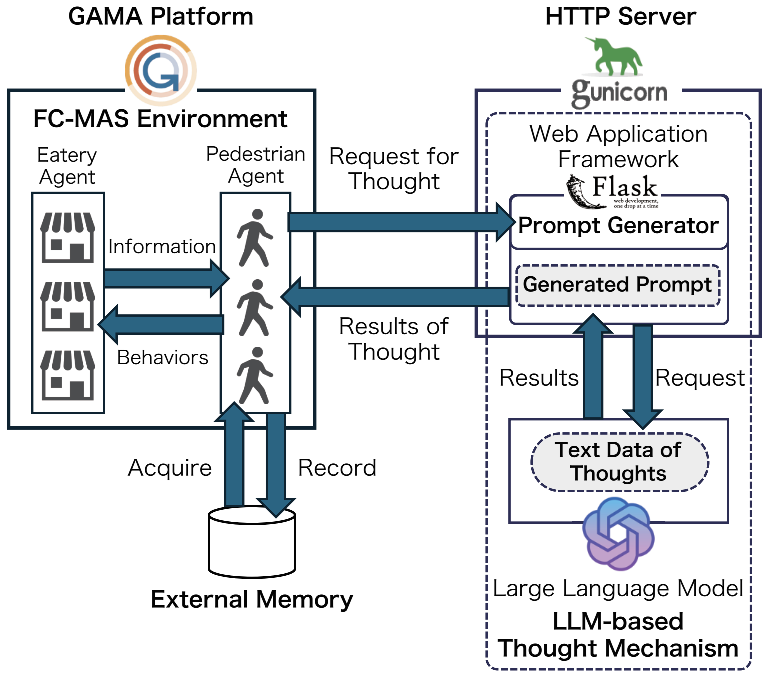

Figure 1: Overview of MAS Environment.

2.2 LLM-based Agent Modeling

Some researchers have endeavored to simulate human societies more realistically by using Large Language Models (LLMs) in constructing agents for simulations, as exemplified by Chat-GPT. The authors of the study (Park et al. 2023) incorporated their own memory system extension to LLMs in building agents capable of executing human-like behaviors including planning. Specifically, they implemented functionalities within agents: "Memory Stream," "Reflection," and "Planning." By integrating these three functions with LLMs, agents became able to accumulate individual experiences during simulation runs and exhibit behaviors consistent with their accumulated experiences and the surrounding environment. They successfully deployed 25 agents in a virtual village, where these agents using natural language interacted based on their experiences, resulting an artificial society.

Thus, the feasibility of creating groups of agents that simulate realistic human populations, that evolve through continuous decision-making and interactions based on LLMs, has been demonstrated. This paper extends the architecture to enable agents to respond based on their preferences and behavioral history, and construct agents integrated with LLMs in a scalable manner, which allows their application to large-scale MASs.

3 MAS ENVIRONMENT INTEGRATED WITH LLM

We extend MAS agents by incorporating mechanisms by basing decision-making processes on LLMs with external memory collaboration, enabling a group of agents to make decisions tailored to individual preferences and behavioral histories in dynamic environments. In this paper, we instantiate and validate an extended group of agents that decide which establishments to enter while navigating through a food court. We refer to this simulation as "Food Court MAS (FC-MAS)."

The simulation environment addressed in this paper is illustrated in Figure 1. Initially, we build a multi-agent simulation environment based on GAMA, an agent-based modeling and simulation platform (Taillandier et al. 2019). GAMA represents not only autonomous agents representing humans but also individual elements of the simulation environment as agents. Interactions among agents and between agents and the environment are processed through message passing on an agent network during simulation execution. The rectangle labeled "FC-MAS Environment" in the figure contains information related to the FC-MAS. The FC-MAS implemented in this paper is designed to represent a food court where pedestrians with diverse attributes gather during lunchtime. There are two types of agents: "pedestrian agent" represents a pedestrian roaming the food court, and "eatery agent" corresponds to an restaurant of the food court. Pedestrian agents decide how to spend their lunchtime while roaming the food court based on decision-making processes that utilize a LLM. Eatery agents accommodate visiting pedestrian agents as customers and, if the eatery is full, request them to join the queue in front of the eatery. In the figure, interactions occur between pedestrian agents and eatery agents, including exchanging information such as queue status (*i.e.,* waiting time), as well as actions like entering the eatery or joining the queue. This paper uses an LLM to enrich the responses of the pedestrian agents.

We enable agents in GAMA to perform "thought for decision-making" via external LLM-based thought mechanisms by using GAMA's ability to communicate with external software. An overview of this implementation is depicted on the right of the pedestrian agent rectangle in Figure 1. Pedestrian agents utilize GAMA's communication ability to access the LLM through an external prompt generator. Text prompts sent via HTTP instruct the LLM to generate appropriate responses for specific tasks. The prompt generator generates LLM prompts based on information received from GAMA, and it handles prompt transmission to the LLM, receiving and processing the results, and transmitting the processed results back to GAMA. Specifically, the prompt generator is implemented in Python as a simple web application executable on the micro web application framework Flask; it operates on the Python HTTP server gunicorn. In this paper, we use Chat-GPT as the LLM, so we integrate the OpenAI library into the prompt generator to facilitate prompt generation and the exchange of generated prompts and results.

The text data generated by the LLM represents a series of thoughts that guide the decision-making process of each pedestrian agent. Pedestrian agents extract conclusions from their thoughts and execute specific actions accordingly. The content of these thoughts is recorded in the external memory of each agent and can be utilized when creating prompts. In the FC-MAS, actions such as considering which eatery to enter based on previous experiences in the food court and ultimately entering the preferred eatery can be achieved through LLM-based thought mechanisms.

4 AGENT MODEL INTEGRATED WITH LLM

To extend pedestrian agents through integration with an LLM, we aim to: 1) generate agent profiles using an LLM, and 2) realize LLM-based decision-making given behaviors derived from individual information and information from the surrounding environment.

4.1 Profile Generation for Pedestrian Agents

To achieve pedestrian agents with realistic and diverse behaviors, the traditional approach of conducting surveys or interviews with real-world individuals to collect fundamental data for model construction is impractical in terms of cost and privacy. Therefore, this paper focuses on the collective intelligence aspect of LLMs and adopt the approach of generating diverse attribute information tailored to the simulation target and using it as agent profiles. In the FC-MAS examined in this paper, multiple pedestrian agents decide how to spend their lunchtime while roaming the food court. We generate profile information including preferences for meals, activities, and various personality traits to simulate the different behaviors of these agents.

The prompt used for profile generation is shown in Figure 2. The "CDL Street" mentioned in the prompt is the name given to the food court in the FC-MAS conducted in this paper. As depicted in the figure, to generate a large number of profiles in unified JSON format, a sample of the profiles is provided first, followed by instructions for profile generation. To create diverse behaviors for agents, profiles are generated containing not only age and favorite foods but also inherent personality traits ("innate"), learned

```
  {
    "name": "Emma Johnson",
    "first_name": "Emma",
    "last_name" : "Johnson",
    "age": "22",
    "innate": "Enjoys problem-solving.",
    "learned": "Computer Science, Mathematics, Linguistics",
    "currently": "Pursuing a degree in Computer Science at Stanford University",
    "favorite food": "Chicken Teriyaki",
    "lifestyle": "Emma Johnson has a break from 12:45 to 14:30 during her classes. She
     always spends this time at CDL Street, savoring her favorite Chicken Teriyaki and
     catching up on the latest tech news.",
    "lunch_plan_req": "1. Maximize break time. 2. Lunch must be at CDL Street.",
    "lunch_start_time": "12:50"
  }
Use the above profile as an example to generate a profile of a virtual person in JSON
format.
Do not change the attribute. Do not make the profile similar to Emma's profile. The
people you generate should be between teens and 80s.
"life style" describes how a person spends the lunch time.
Select the appropriate location from the following Place options on the CDL Street.
Place options: Brasserie A, Cafe B, Japanese B, Chinese B, Ramen B, Japanese A,
Chinese A, Italian A, Spanish A, Ramen A, Cafe A
Do not use the following names: <name_list>
```

Figure 2: Example of profile generation prompt.

knowledge and skills ("learned"), current status ("currently"), and lifestyle aspects related to how they spend their lunchtime. Since the detailed mechanisms of LLM behavior are not fully understood, demonstrating the validity of our profile generation method is challenging. Therefore, in this paper, we refer to the profile items mentioned in the literature (Park et al. 2023); they confirm that a large number of diverse characters could be generated.

In FC-MAS, prior to running the simulation, diverse profiles are generated based on the prompt shown in Figure 2 and each agent is assigned a different profile. Agents then contemplate actions to take based on their assigned profiles.

4.2 Decision-making Process on Behaviors of LLM-based Agents

In the initial state, pedestrian agents are positioned at the entrance of the simulated food court called "CDL Street" within the simulation environment. The layout of CDL Street is illustrated in Figure 4. The yellow rectangles represent eateries, with labels denoting restaurant type (*e.g.,* "Japanese A" denotes a Japanese restaurant). The numerical values below the labels indicate the level of crowding, with "17/20" indicating that 17 out of 20 seats are occupied. Within this MAS, there are agents that execute predetermined actions without LLM integration, depicted as blue circles in the figure. On the other hand, LLM-based agents are represented by red circles.

4.2.1 Action Flow of Agents

Figure 3 illustrates the action flow of pedestrian agents in FC-MAS. The actions in red frames represent the part where thinking is executed using LLM. Upon arrival at CDL Street or when a destination update is required, agents decide which eatery to head to. Through LLM-based deliberation, if a decision is made to opt for an eatery not within the target environment (CDL Street), such as quickly grabbing lunch at a food truck or convenience store, the agent transitions to "Exit Environment" and leaves CDL Street.

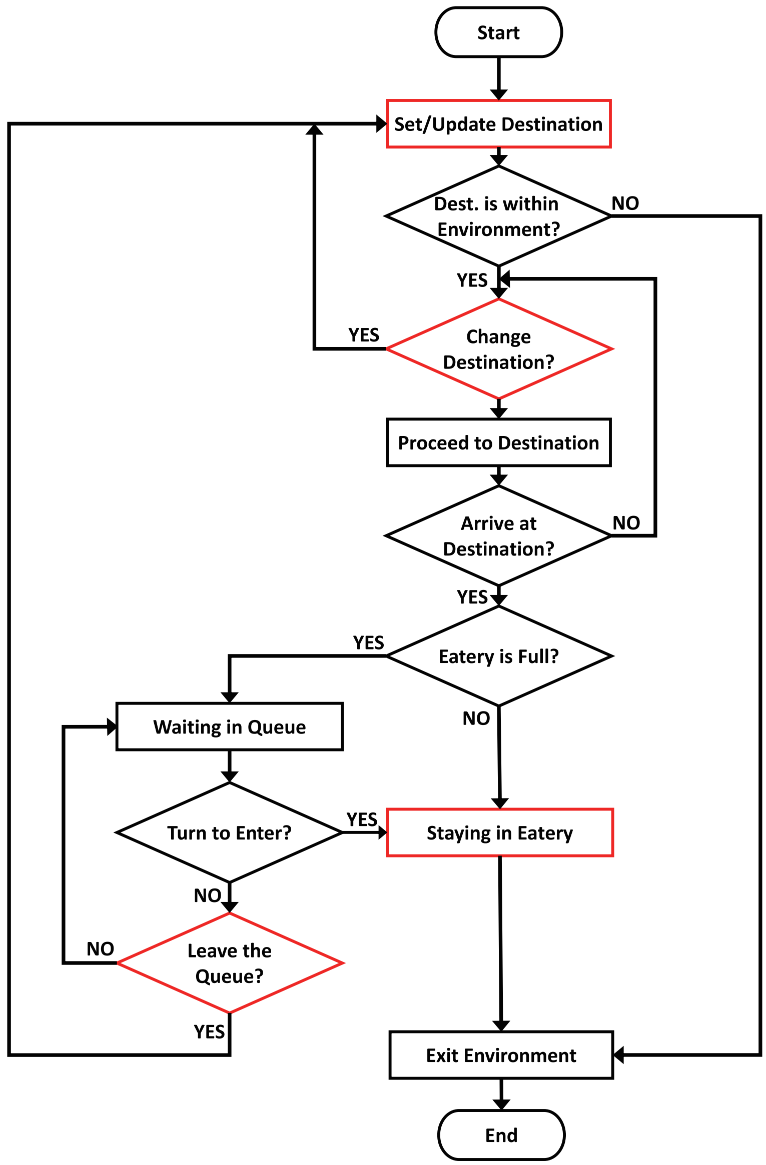

Figure 3: Action flow diagram of pedestrian agent.

If an existing eatery is chosen, the agent begins moving towards it. During the trip to the destination, the agent dynamically assesses whether to keep or change the current destination based on environmental information. Upon reaching the desired eatery, if there is a vacant seat, the agent enters; otherwise, if the eatery is full, the agent temporarily joins the waiting queue and evaluates whether to continue waiting or search for another eatery at regular intervals (in this paper, every 5 minutes). Furthermore, upon entering an eatery, the agent calculates the duration of stay based on its basic information. Once the stay duration is exceeded, the agent leaves the eatery and exits CDL Street.

Pedestrian agents possess an external memory that records their individual thoughts and environmental information. The content of the memory is recorded in natural language expressions along with timestamps. This information is transmitted from the agents to the prompt generator and used during prompt generation. Throughout the simulation, pedestrian agents primarily acquire environmental information related to eateries. In this paper, pedestrian agents gather information about eateries within a radius of 10 meters around them

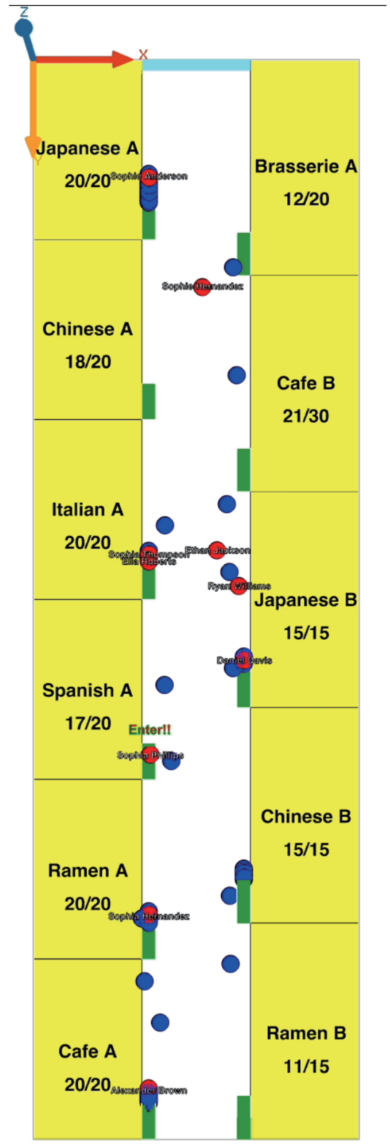

Figure 4: Screenshot of CDL street.

every 10 seconds of simulation time. Eateries have static and dynamic data. The former includes invariant details such as the eatery's name, average meal cost, and popular menu items. The latter comprises dynamically changing data, such as the number of people waiting in line, which is recorded in natural language expressions, *e.g.,* "There are about 5 people waiting in line outside Cafe A," and stored in memory.

4.2.2 Prompt Generation for Making-Decision

In the execution steps, the red frames in the action flow diagram of Figure 3, agents attempt to execute LLM-based thoughts yielded by the prompt generator and make decisions on the next behavior. The composition of generated prompts is broadly categorized into 1) individual information and environmental information relevant to thoughts, and 2) the policy for generating thoughts. "Individual information and environmental information relevant to thought" includes the following details.

```
2023-12-25 12:48:23: Alex Martinez arrives on CDL Street.
2023-12-25 12:48:23: I'm craving sushi today, and Japanese Ahas the best sushi in
town. Plus, I might get some design inspiration while I'm there.
2023-12-25 12:48:40: There is 1 person waiting in line outside the Japanese A.
2023-12-25 12:48:40: I'm glad there's only 1 person waiting in line at Japanese A.
Hopefully, I won't have to wait too long to satisfy my sushi craving and get some
design inspiration.
2023-12-25 12:48:50: Alex started waiting in line at Japanese A.
                :
                :
```

Figure 5: Example of the information recorded in agent's memory.

- Basic Information of Pedestrian Agent
- Basic Information of Eatery
- Contens of Agent's Memory
- Description of Life-style
- Options for Destination

"The policy for generating thoughts" articulates the guidelines for determining how one of multiple options will be selected. For instance, when deciding which eatery to head to, phrases such as "Which store will Agent Name head to? Also, state the sentence in Agent Name's head at that time." are documented after "individual information and environmental information relevant to thought." Figure 6 provides an example prompt for executing thoughts when an agent selects an eatery. As illustrated in this example, individual information based on profiles necessary for thought, accumulated restaurant information, and other information stored in memory are described first. Following this, two questions are posed to initiate thought: "Where is the agent heading next?" and "What is the agent thinking at this moment?" The destination determined from these questions and the agent's thoughts at that time are sent to the simulation side and applied to the move agents within the simulation.

5 EXPERIMENT

We introduced above agent models with diverse behaviors based on LLM, utilizing individual information, stored memories, and surrounding environment, into the FC-MAS. We conduct here experiments to verify how individual thought mechanisms based on LLM influence agent movements and their surroundings. This experiment simulated a total of 1,000 pedestrian agents, consisting of 100 LLM-based pedestrian agents and 900 pedestrian agents following predefined behaviors without LLM integration.

5.1 Description of Experiment

We aim, in this experiment, to introduce pedestrian agents making decisions based on LLM into FC-MAS, and verify whether the agents can take actions aligned with their own attributes and surrounding environmental information. Additionally, we aim to investigate whether the verbalization of situations using LLM makes understanding and grasping agent behaviors in the simulation process relatively easier; both are difficult to infer if the MAS uses abstract agent models. Specifically, we conduct the verification from two perspectives: (a) the validity of agent behavior and decision-making, and (b) the impact of agent behavioral individuality on the collective behavior of the population. For (a), we examine the attribute information possessed by agents and the memory logs at the end of the simulation to analyze agent behavior and intention. We confirm whether the agents ' decisions, based on natural language expressions, were understandable to humans. In other words, we verify whether decisions and behaviors are reasonable in terms of their rationale, even if they lack efficiency or rationality. For (b), agents are assigned attribute

```
/* === Individual info. and environmental info. relevant to thoughts === */
/* Basic Information of Pedestrian Agent */
Name: Emma Johnson
Age: 22
                :
/* Basic Information of Eatery */
Emma is now at CDL Street where the folloing restaurants are lined up.
Restaurant options:
Japanese A: Average price is $20. Popular dishes is Tempura.
Italian A: Average price is $19. Popular dishes is Pastas.
                :
/* Memory */
Here are Emma's memories and thought in chronological order.
2023-12-25 12:51:10: Emma Johnson arrives on CDL Street.
                :
/* Life-style */
Emma Johnson has a break from 12:45 to 14:30. She always spends this time at CDL
Street. savoring his favorite Chicken Teriyaki and catchingup on the latest tech
news.
                :
/* Options for Destination */
Place options: Brasserie A, Cafe B, Japanese B, Chinese B, .......
                :
/* === The policy for generating thoughts === */
Which place will Emma head to?
Also, state the sentence in Emma's head at that time.
Please state in the following format, verbatim.
----
{"place": "####", "sentence": "####"}
----
```

Figure 6: Example of prompt for executing thought.

information related to individual elements such as personality traits and characteristics. We compare and verify the results of two simulations that use different attribute information to understand how changes in individual behavioral characteristics influence the collective behavior of agents as a group.

5.2 Experimental Results

5.2.1 Result 1: Validity of Agent Behaviors and Decision-Making

The verification results gained from observations of the behavior of pedestrian agent "Alex Ramirez" are described below. First, the observed behavior of the agent, inferred from the simulation logs, is as follows:

> Upon arriving at CDL Street, Alex proceeded straight to "Spanish A", but upon reaching the front of the it, paused briefly, then retraced his steps to "Italian A" next door, where he entered and stayed.

To understand the intention behind this sequence of actions, a specific investigation was conducted by referencing the contents of the agent's memory. Below is a partial excerpt from Alex's memory at the end of the simulation:

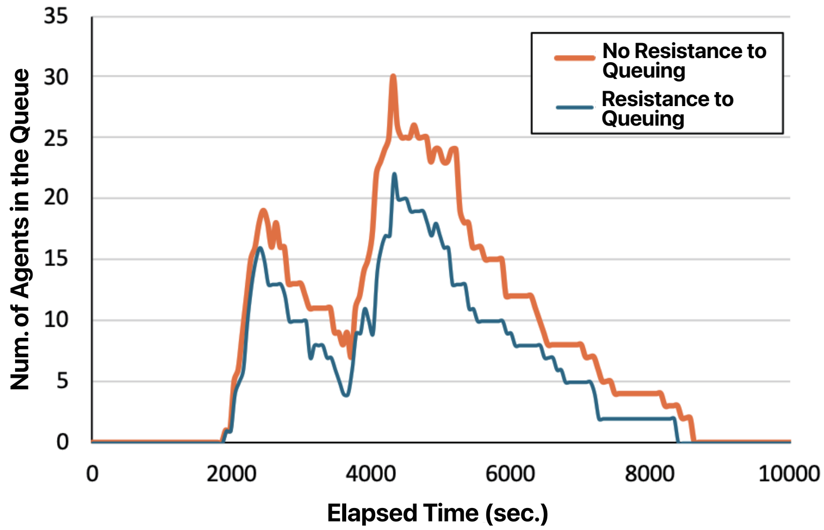

Figure 7: Transision of the number of queueing agents.

- *There are about 13 people waiting in line outside Spanish A. I hate standing in line and I only have 44 minutes left for my lunch break. I should change my destination from Spanish A.*
- *I should go to Italian A instead. I can enjoy pasta there and hopefully avoid the long line at Spanish A.*

From these thought processes, it can be understood that Alex resisted joining the queue and instead changed the destination to "Italian A" due to the short lunchtime of only 44 minutes. Similar examinations of the behaviors and internal states of memory were conducted for other agents, revealing that they also exhibited actions appropriate for their personal attributes and environmental information at the time of decision-making.

5.2.2 Result 2: Impact of Agent Behavioral Individuality on the Collective Behavior

We conducted an analysis of the impact of modifying the personal information of pedestrian agents based on LLM on the collective behavior of agents. Simulations were performed for two scenarios: one where all agents had a "no resistance to queuing" personality while in the other all had a "resistance to queuing" personality, and the number of people in each queue was compared. Modification of the personal information was simply achieved by adding one of the following sentences to the "life style" and "innate" attributes of each pedestrian agent's basic information:

- {Agent Name} doesn't mind standing in line.
- {Agent Name} hates standing in line.

The transition in the number of agents in the queues for each scenario is shown in Figure 7. From the results depicted in the graph, it is evident that the simulation with the "resistance to queuing" scenario generally saw fewer people queuing throughout the entire period compared to the "no resistance to queuing" scenario.

We discuss the results as follows. Regarding the validation of agent behavior and decision-making, we were able to confirm and understand the intentions and background information behind agents' behaviors by referencing their past thoughts and experiences stored in memory. MAS that use coarse-grained agent models make it difficult to understand agent behavior. For instance, in models that employ relatively simplistic decision-making methods with randomness, such as Monte Carlo methods, agent behavior is explained as just probabilistic events. However, in the approach outlined in this paper, a series of circumstances regarding behaviors can be presented in a format that is understandable to humans. This characteristic is particularly beneficial in participatory simulations, where human participants are involved in the simulation process, as it facilitates obtaining agreement from human participants.

Furthermore, in verifying the impact of agent behavior differences on collective behavior, we confirmed that by altering the individual attributes that agents reference when making decisions, there are explicit changes in the collective behavior of agents even though the verification was conducted using simple simulation scenarios. The potential to describe elements such as personality and character, which were traditionally difficult to handle as parameters in conventional agent models, as information representing agent behavior differences in natural language expressions, demonstrates the impact of individual thoughts and decisions on the collective behavior of agents. From these observations, we argue that the approach presented in this paper, incorporating LLM-based thought mechanisms into agent models, is beneficial for realizing simulations that consider the diverse characteristics of individual humans.

6 DISCUSSION

In this paper, we demonstrate multi-agent simulations where in an agent's decision-making processes can be directed by a LLM. We further illustrate how the output of the LLM can be accurately reflected in an ongoing simulation in real-time using a straightforward simulation scenario. Controlling the behavior of LLMs remains a well-known challenge (Liu et al. 2024), and evaluating the validity of LLM-based agent behaviors is inherently complex. As presented in Section 5, we validated agent behavior by assessing the consistency between their actions and the natural language explanations held in their memory. Due to the time-consuming nature of our manual validation approach, there is a pressing need for the development of efficient or automated validation methods.

As a possible candidate, we are currently exploring an interview-based semi-automated approach. In the simulation conducted in Section 5, there was an agent named "Benjamin Thomas" who did not stay at Cafe A during the simulation. The following Q&A was obtained through an interview with "Thomas."

Q: Please describe your experience while staying at Cafe A.
A: I did not stay at Cafe A, so I am unable to provide any feedback on the experience.

This interview, although brief, confirms that the agent does not provide answers based on experiences it has not had or memories it has not stored. Inspired by this result, we will further develop the semi-automated validation method using interviews to identify the foundations of decision-making.

It is fundamentally unclear what kind of data is included in LLMs and how their outputs are produced. Consequently, it is challenging to prove and explain that the agent behaviors obtained through our proposed method are reasonably general with regard to determining a place to have lunch. Bridging the gap between LLMs and reality is one of our future research directions.

7 CONCLUSION

In this paper, we propose a method for constructing agents capable of generating diverse decision-making and corresponding thoughts based on various behavioral individualities, through integration with Large Language Model, and executing Multi-Agent Simulations incorporating such agents. We conducted simulations mimicking the selection of eateries, a daily activity in real-life, and through verification of behavior and outcomes, we confirmed that agents made a variety of decisions based on their assigned preferences and memories acquired during the simulation process.

A specific advantage of our proposed method is that it enables agent modeling that captures diverse individualities. Traditionally, achieving such diversity has been challenging due to the extensive real-life data collection needed. However, there are issues with LLM-based agent models, including the validity and sophistication of LLM-oriented decision-making.

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REFERENCES

Axelrod, R. 1984. *The Evolution of Cooperation*. New York, Basic Books.

Cheng, S.-F. and T. D. Nguyen. 2011. "TaxiSim: A Multiagent Simulation Platform for Evaluating Taxi Fleet Operations". In *Proceedings of the 2011 IEEE/WIC/ACM International Conferences on Web Intelligence and Intelligent Agent Technology (WI-IAT 2011)*, August 22nd-27th, Lyon, France, 14-21.

Fujii, H., H. Uchida, and S. Yoshimura. 2017. "Agent-Based Simulation Framework for Mixed Traffic of Cars, Pedestrians and Trams". *Transportation Research Part C: Emerging Technologies* 85:234–248.

Hattori, H., Y. Nakajima, and T. Ishida. 2011. "Learning from Humans: Agent Modeling with Individual Human Behaviors". *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans* 41(1):1–9.

Kumar, R. R., P. Varakantham, and S.-F. Cheng. 2023. "Strategic Planning for Flexible Agent Availability in Large Taxi Fleets". In *Proceedings of the 2023 International Conference on Autonomous Agents and Multiagent Systems (AAMAS-2023)*, May 29th-June 2nd, London, United Kingdom, 552-560.

Kurahashi, S. 2023. "Assessment of the Impact of COVID-19 Infections Considering Risk of Infected People Inflow to the Region". In *New Frontiers in Artificial Intelligence*, edited by K. Yada, Y. Takama, K. Mineshima, and K. Satoh: 382-392, Cham, Springer Nature Switzerland AG.

Liu, J., C. Yu, J. Gao, Y. Xie, Q. Liao, Y. Wu *et al*. 2024. "LLM-Powered Hierarchical Language Agent for Real-time Human-AI Coordination". In *Proceedings of the 23rd International Conference on Autonomous Agents and Multiagent Systems (AAMAS-2024)*, May 6th-May 10nd, Auckland, New Zealand, 1219-1228.

Nagel, M. and M. Schreckenberg. 1992. "A Cellular Automaton Model for Freeway Traffic". *Journal of Pysics I France* 2(12):2221–2229.

Park, J. S., J. O'Brien, C. J. Cai, M. R. Morris, P. Liang, and M. S. Bernstein. 2023. "Generative Agents: Interactive Simulacra of Human Behavior". In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology (UIST-2023)*, October 29th-November 1st, San Francisco, USA, 1-22.

Sánchez, N. C., I. Martinez, L. A. Pastor, and K. Larson. 2022. "On the Simulation of Shared Autonomous Micro-Mobility". *Communications in Transportation Research* 2:100065.

Taillandier, P., B. Gaudou, A. Grignard, H. Quang Nghi, N. Marilleau, P. Caillou, *et al*. 2019. "Building, Composing and Experimenting Complex Spatial Models with the GAMA Platform". *GeoInformatica* 23:299–322.

Yamashita, T., T. Okada, and I. Noda. 2013. "Implementation of Simulation Environment for Exhaustive Analysis of Huge-Scale Pedestrian Flow". *SICE Journal of Control, Measurement, and System Integration* 6(2):137–146.

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